International Journal of Innovative Computing, Information and Control
Volume **20**, Number **3**, June **2024** ISSN 1349-4198
pp. 821–838

A MULTIVARIATE VAR MODEL FOR THE SUSTAINABLE DEVELOPMENT OF THE INDUSTRIAL SECTOR ECONOMIC

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Received December 2022; revised April 2023

Abstract. *The industrial economy fluctuates with market trends, production ability, product utilization, etc. For stabilized economic sustainability, different influencing factors are to be considered with the varying time series information. Handling fluctuating information requires multivariate functions for precise identification of economic sustainability. Therefore, this manuscript introduces a Multivariate Data Processing Model (MDPM) using Vector Autoregression (VAR) for balancing the fluctuating factors. The proposed model extracts differential information from varying time series related to the industrial economy. This includes production, transportation, supply, and market analysis data. This data is invariantly handled using VAR in two different steps. First, the relation between the distinct factors based on time series is framed. In the second step, the regression model for filtering the hike/increase in the relation output is performed. The relationship is set as a benchmark for economic sustainability based on the improvement. The proposed model identifies incremental output post the forward time-series data for preventing sustainability falls. This model is validated using the metrics sustainability factor, processing rate, variation, processing time, and failures.*
Keywords: Economic sustainability, Industrial sector, Multivariate data, Time series, VAR model

1. **Introduction.** Industrial sector development is a process that uses premises for processing, serving, manufacturing, and storage activities. Industrial sector development is an important task to perform in every organization. Industrial sector development improves the country's and organization's overall economic growth [1]. Industrial sector development is mostly done based on factors and resources which are required to perform certain tasks in the industry. The actual goal of industrial sector development is to increase an organization's Total Factor Productivity (TFP) range [2]. The industry's Gross Domestic Product (GDP) rate is evaluated based on the sector development process. GDP provides feasible data which contains the exact information and features of products. GDP produces the necessary information for economic growth [3]. Economic models are also used in industrial sector development systems. An analysis technique is implemented in models that identify the important factors and patterns for further development processes. Sustainable development ranges are estimated based on certain conditions and functions. GDP improves an organization's economic status, reducing the financial instability ratio in industries [4,5].

The Vector Autoregression (VAR) model is mostly used to capture or record the relationship among multiple quantities. VAR model provides necessary data for further time series process [6]. VAR is a multivariate time series model that enhances the systems'

DOI: 10.24507/ijicic.20.03.821

overall performance and feasibility range. The VAR model is used in industrial economic development systems. The VAR model produces the dynamic relationship between an organization's economic and financial development ratio [7]. The VAR model reduces the error and latency levels in identification, improving the system's efficiency. The VAR model provides exact evidence of relationships that create an impact on the industrial economic development process [8]. The VAR model produces important content and information required for economic development systems. The VAR model identifies the updated time series of industries that provide appropriate information for economic growth development processes. VAR also predicts the important sustainable economic development concerns presented in the industry. The VAR model reduces the overall complexity ratio in industrial economic development systems [9,10].

Vector Autoregression (VAR) models are among the most widely used, flexible, and user-friendly methods for studying multivariate time series. The research models and forecasts the simultaneous development of both short- and long-term inter-firm ties using a VAR analysis. Throughout the last generation, VAR models have seen widespread usage in socioeconomic studies. The study of a time series with just one predictor variable, time, is called a univariate time series analysis. The variables in a multivariate series change with time. Multivariate time series analysis is used to better understand the interrelationships of many time series variables. When it comes to multivariate time analysis, the VAR model is by far the most adaptable and productive option.

Vector Autoregression (VAR) methodology is mostly used for sustainable industrial economic development systems. The VAR method increases industry's and organizations' economic and financial growth [11]. The VAR model identifies the location of information and variables presented in the database. The VAR model provides feasible data for the sustainable industrial economic development process [12]. Economic development requires effective datasets that create an effective idea to enhance an organization's or industry's economic growth. VAR estimators and detectors are used in industries for the data analysis process [13]. Data analysis produces relevant data which are extracted from the database. VAR estimator detects the exact contents which are required for the economic development process. VAR estimators reduce development systems' overall time and energy consumption range [14]. VAR provides certain solutions to problems that occur during development and management processes. VAR solutions enhance the energy efficiency range of an organization that improves the sustainable industrial economy development ratio [15].

Multivariate time series may be modeled using VAR models, which extend the single-variable (univariate) autoregressive model. It predicts a rising trend in energy consumption, GDP, and emissions. Vector autoregression is used in a multivariate statistical processing model to equalize the effects of several variables. These elements might act autonomously of one another. These factors often influence one another's development inside the system. In this study, mathematics simulate the interplay between these systems and investigate their dynamics [16]. It is common practice to construct a Vector Autoregression (VAR) model for a multivariate system to investigate its long-term and short-term dependencies. As a result, the model may be put to use in making predictions about the system.

The primary contributions of the work include the following.

1) The paper presents a Multivariate Data Processing Model (MDPM) that uses Vector Autoregression (VAR) to dampen the effects of these potentially disruptive variables. The suggested model uses a variety of time series data about the industrial sector to derive asymmetric data.

2) The next step is to implement a regression model to screen out the growth/increase in the relational output. The suggested methodology utilizes forward time-series data to pinpoint incremental production that may be used to forestall drops in sustainability.

3) Statistical analysis of the experimental data demonstrates that the suggested approach decreases processing time and increases success rate while simultaneously increasing sustainability.

The article continues with the following structure: The literature is discussed in Section 2. Section 3 discusses the methodology and data sources of the Multivariate Data Processing Model (MDPM) that use Vector Autoregression (VAR) to stabilize the varying components. The experimental data and analysis are presented in Section 4. A summary and recommendations for further research are included in the last Section 5.

2. **Related Works.** de Lima [17] proposed a new Twitter analytics framework for the Circular Economy (CE) development process. Twitter analytics combines the content, network, and descriptive to identify the exact meaning of the content. The exact data provide optimal information for further processes in CE, reducing the development process's complexity. Twitter analytics reduces both the time and energy consumption ratio in the computation process. The proposed framework provides feasible data for CE development systems. The study offers researchers and professionals in the field critical thoughts that help illuminate the nature of the CE, its proper use, and its significance.

Wu et al. [18] introduced a multivariate coupled economic model hydrogen production project. The main aim of the introduced model is to predict hydrogen production using renewable energy with off-peak electricity. Key coupling variables are detected from projects producing relevant production systems data. Carbon emission price, hydrogen price, and renewable energy hours are used here that reduce the energy consumption range in identification and optimization processes. The findings suggest that the important coupling factors in the site selection stage are hydrogen pricing, renewable energy utilization hours, and integrated tariff, which are influenced by both renewable energy and off-peak grid power.

Bressanelli et al. [19] proposed a new evaluation method for the Circular Economy (CE) and industrial districts. Supply Chain (SC) structures are used in the evaluation method that predicts the exact relationship among the contexts. SC produces the necessary information for the evaluation method, which achieves high accuracy in economic development systems. SC structure links the variables which are extracted that provide effective information for the development process. Finally, the research establishes a bridge between previous works that focused on different aspects of the circular economy transition, supply chain structure, and interactions, and the transformation trajectories of mature industries, allowing for a more nuanced comprehension of the interplay between these phenomena. The proposed method enhances the efficiency ratio of industrial districts.

Norouzi et al. [20] developed a scientific evolution analysis for the Circular Economy (CE). The main aim of the proposed analysis is to identify the impacts of CE in the building and construction sectors. The proposed analysis is mostly used in smart cities that require proper analysis for various processes. New highlights and trends are detected, which provide relevant data for CE development systems. Multivariate statistical analysis is also used here that provide necessary information for the evolution process. Based on the findings of this assessment, there is a clear need to fill important knowledge gaps and advance holistic methods to ready mass wood building for the circular economy.

Halkos et al. [21] proposed an evidence-based complex index for Inclusive and Green Industrial Performance (IGIP). The actual goal of a complex index is to capture the dimensions and variables of the world's economic development process. Expanding access to financial services has the potential to boost green economic competence, as seen by the results. This is accomplished mostly by limiting the availability of credit to businesses that produce carbon emissions. More than anything else, the findings have implications for how one goes about implementing a plan for financial growth and how one keeps relations between the government, financial institutions, and enterprises in good shape. The proposed index increases the green industrial performance range that maximizes the economic level of an organization.

Xu et al. [22] designed a multi-objective optimization model for an industrial structure adjustment system. The proposed model is mainly used to adjust the structure of industries. Slack variables and features are extracted that improve the accuracy of the industry adjustment process. The proposed model provides effective information and variables for energy-economic development systems. With appropriate optimization and modification of the industrial structure, the advantages to the economy, society, and the environment are all realized in the form of growth, as shown by the findings. Experimental results show that the proposed model maximizes economic growth and reduces the energy consumption ratio of industries.

Eglash et al. [23] introduced an Artificial Intelligence (AI) based automation model for the artisanal economy development process. Human-machine collaboration is used in the automation model that reduces the overall complexity of product production. Various automation techniques are used here that provide relevant services to perform tasks in artisanal economy development systems. The introduced automation model improves the performance and effectiveness range of the artisanal economy.

Kim and Nam-Chol [24] presented a pilot scale-eco-county for the Circular Economy (CE). The proposed method's main aim is to reduce a country's environmental burden and pollution range. The proposed method is most widely used in various countries to solve environmental problems. Certain conditions are implemented in the proposed method that provides feasible data for the economic development process. Pilot scale-eco-county is introduced to countries to improve the overall CE range.

Dong et al. [25] proposed a new systematic approach to a Circular Economy (CE). The proposed approach is mostly used to address the urban sustainability problems which are presented in CE. Sustainable Development Goals (SDGs) are implemented here that provide feasible data for the detection process. SDG also produces urban scopes and variables for a systematic approach. The proposed approach achieves high accuracy in the urban sustainability prediction process.

Chen et al. [26] developed a multivariate compositional data model for structural prediction and analysis. The main aim of the proposed model is to identify the structure of sub-industrial energy consumption. Gray wolf optimizer is implemented here that identifies the optimal values and features which are required for further processes. Wolf optimizer reduces both time and energy consumption range in the economic development process. Compared with other models, the proposed model maximizes prediction accuracy, enhancing the systems' performance.

Zhang et al. [27] proposed a Multivariate Nonlinear Regression (MNR) based production capacity identification and analysis method. The Affinity Propagation (AP) clustering algorithm is also used in the analysis method that extracts the production capacity from the database. The proposed method is mainly used to improve the energy-saving ratio in industries. AP clustering algorithm reduces latency in the production capacity identification process. The proposed method maximizes the accuracy of allocation and scheduling processes, reducing production systems' overall complexity level.

Zhu et al. [28] introduced a Machine Learning (ML) based evaluation method for industry agglomeration. ML algorithm predicts the necessary information for the evaluation process. ML also identifies the exact relationship between regional economic and industrial integration development processes. The identified data provide feasible data for further processes. Experimental results show that the proposed method achieves high accuracy in industry agglomeration detection that improves the performance of the systems.

3. **Proposed Processing Model.** For stabilized economic sustainability, different influencing factors are to be considered with the varying time series information. The industrial economy fluctuates with market trends, production ability, product utilization, etc. Handling fluctuating information requires multivariate functions for precise identification of economic sustainability. Therefore, this manuscript introduces a Multivariate Data Processing Model (MDPM) using Vector Autoregression (VAR) for balancing the fluctuating factors. VAR is a model used to acquire the relationship between the time series data that change over time. VAR is a type of continuous process model when it generalizes the discriminant autoregression model by allowing for multivariate time series. In this VAR model, the time series data has an equation sculpting its evolution over time. Vector Autoregression (VAR) models are used for multivariate time series and the structure which has variable is a linear function of lags of itself and lags of other variables. The VAR model relates the present observations of the given data and the fast observation of other data with the industry multivariate autoregressive models, which expands their procedureto multiple time series, so that the vector of present values of all data has been modeled as linear and the sum of previous activities. VAR in multivariate time series is used to analyze the system's variance, factor, and cluster. VAR is useful in predicting multiple time series variables using a single model in the industry. The proposed model extracts differential information from varying time series related to the industrial economy. VAR is a procrastinating algorithm that can be used when two or more time series influence each other. It is used to observe the time of the demand, supply, and production data extracted from the industry. VAR for multivariate series allowed the simultaneous verification of data when provided by the industry between dynamic processes and the individual difference and gained increased concession in the present years. The proposed VAR-based model is portrayed in Figure 1.

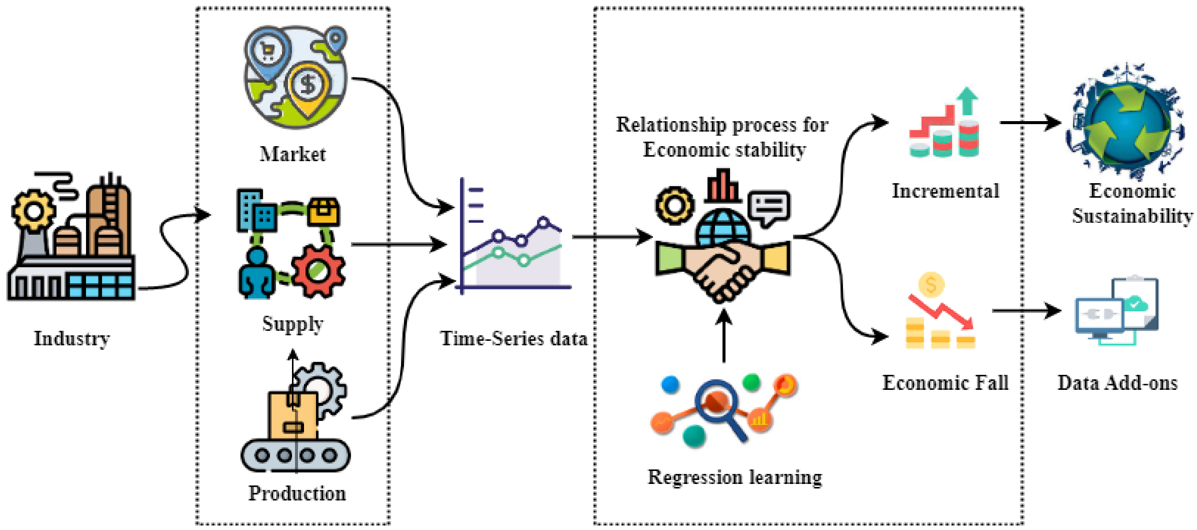

Figure 1. Proposed VAR-based model

Here in this model, the time series data are collected from the industry of the process of VAR learning. The proposed model extracts the differential information from varying time series related to the industrial economy. This includes production, transportation, supply, and market analysis data. There are time series data in which the time is observed for the extracted factors from the industry. Then VAR learning is used to find the relationship between the industry-extracted data, known as the time series data. The data is invariantly handled using VAR in two different steps. First, the relation between the district factors based on time series is framed. In the second step, the regression model for filtering the hike/increase in the relation output is performed. The relation of the time series data can be classified into incremental and fall based on the economic outcome of the industry. From the increased economic development outcome, sustainability can be identified where the maximum target is set as a benchmark for the upcoming process. From the output of the fall of the relationship between the time series data, the data add-on process will be done by adding up the time series data. Based on the improvement, the output of the relationship process is set as a benchmark for economic sustainability. The proposed model identifies incremental output post the forward time series data for presenting sustainability falls. From the industry, the time series data can be extracted. The market, transportation supply, and production data are known as time series data. In this, the time of the data which is extracted from the industry is observed. Time series data is the collection of observations obtained through a repeated process over time. The following equation explains the process of extracting the time series data from the industry.

$$\varphi_\alpha = \delta a_Q + \gamma M_Q + \varepsilon_T^1 x_{Q-1} + V_Q^T \tag{1}$$

where φ_α is denoted as the collection of time series data, δa_Q is the calculation of the market data for multifunctional data δ from the industry, γM_Q is denoted as the calculation of supply data of non-integer factorial function, $\varepsilon_T^1 x_{Q-1}$ is denoted as the production data from industry with Q mean at a time T, and V_Q^T is denoted as the calculation of the time observed for the extracted factors. Now the data is invariantly handled using VAR in two different steps. First, the relation between the distinct factors based on time series is framed. If the price is high, the demand reduces, if the demand increases on this criterion the relationship process takes place. The relationship process is done for the factors which are extracted from the industry. The time series of the factors which is extracted from the industry is helpful in the process of finding the relation between the data. VAR learning is used to handle the data extorted from the time series data in the industry. VAR learning is used in the multivariate time series, which helps analyze the variance, factor, and cluster of the industrial system. VAR for multivariate series allowed the simultaneous verification of data when provided by the industry between dynamic processes and the individual difference and gained increased concession in the present years.

VAR learning which is used in the classification of the data by finding the relation between the distinct factors helps in observing the time of the data which is produced by the industry. This learning algorithm helps in finding the continuous observation of the time series data for the procedure of finding the relation between the factors. VAR is a procrastinating algorithm that can be used when two or more time series influence each other. It is used to observe the time of the demand, supply, and production data extracted from the industry. The VAR helps in finding the time taken for the factors to obtain its features in the industry to improve economic development. Then that time is observed for the process of verifying the relationship between the time series data from the industry. The market data denotes the number of chattels required for the consumers, transportation data represents the process of acquiring and preparing the stuff to deliver for the further process and the production data denotes the manufacturing process of the entire chattels. Autoregression learning is used to determine the sustainability of economic development in the industry through the relationship process. From the time series data, its features can be classified to detect the economic status and the further steps to prevent sustainability falls. The process of acquiring the time series data for finding the relation between the distinct factors of economic increment and fall through the VAR model $\varphi_{\alpha 1}$ and a_Q is explained by the following Equations (2) and (3):

$$\varphi_{\alpha 1} = \lambda a_Q + \beta M_Q + \varepsilon_R^1 x_{Q-1} + V_Q^R \tag{2}$$

$$a_Q = \rho_Q^M + \psi M_Q + \varepsilon_a^1 x_{Q-1} + V_Q^a \tag{3}$$

where λa_Q denotes the output of the time series data, βM_Q denotes the amount of time required for the factors, ρ_Q^M is denoted as the process of finding the relationship through the VAR model, ψM_Q is denoted as the amount of production data, a_Q is represented as the number of chattels, and R is denoted as the supply data. In the second step, the regression model for filtering the hike/increase in the relation output is performed. The relationship identification from the acquired data [as in Equation (1)] is presented in Figure 2.

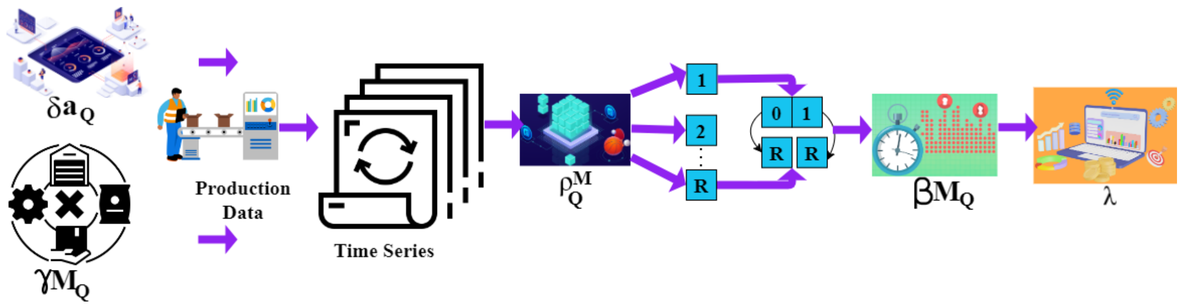

FIGURE 2. Relationship identification

Now from the output of the relationship process, the incremental or the fall of economic sustainability can be found. The increment of the relationship constitution makes the high economic stability. This includes production, transportation, supply, and market analysis data. If the time series data is increased in the relationship, then the economic development is stable and it can be set as a benchmark. Regression learning is used to filter the hike in the related process to get a high output for the process of economic development. The increased relationship output results in increased economic stability; the output can be fixed as a yardstick for the upcoming processes. The output of the relationship between the distinct factors helps in finding the economic development status by classifying them into incremental and the fall of sustainability (Figure 2).

The VAR model helps in classifying the time series data by finding the relationship between factors and classifying the output by the increase or fall of economic stability. This data is invariantly handled using VAR in two different steps. First, the relation between the distinct factors based on time series is framed. In the second step, the regression model for filtering the hike/increase in the relation output is performed. The increased economic development of the industry helps in the static sustainability of the economic level. The process of finding the relationship between the distinct factors helps in the identification of the hike of the output by using VAR learning. This can improve the industrial economy, which includes production, transportation, supply, and market analysis data. The time series uses the data to find the relation between the factors in the industrial sector. The relation of the time series data can be classified into incremental and fall based on the economic outcome of the industry. The data such as production, transportation, supply, and market analysis data are used through the time series data for the process of identifying the increased hike of the relation output. In time series data, the VAR model's classification process occurs. The process of filtering the hike of the relation output is explained by the following Equations (4) and (5):

$$G_{A_Q} = H_{x_{Q-1}} + V_Q \tag{4}$$

$$\left.\begin{array}{r} G = \begin{bmatrix} 1 & -\lambda & -\beta \\ -\rho & 1 & -\psi \\ 1 & -\delta & -\gamma \end{bmatrix} \\ v_Q = \left(v_Q^R, v_Q^a, v_Q^T\right)' \\ H = \begin{bmatrix} H_R' \\ H_a' \\ H_T' \end{bmatrix} \end{array}\right\} \tag{5}$$

where G_{A_Q} is denoted as the output of the relationship process, and $H_{x_{Q-1}}$ is represented as the calculation of the hike of the relation output. Now the fall of economic stability can be found using the relationship process output. The deflation of the economy occurred due to the insufficient observation of the time series data. The relation of the time series data can be classified into incremental and fall based on the economic outcome of the industry. From the output of the fall of the relationship between the time series data, the data add-on process will be done by adding up the time series data. This may vary according to the features of the factors extracted from the industry. If the data from the industry is not obtained according to the time of the process, then it leads to the fall of economic stability. Handling fluctuating information requires multivariate functions for precise identification of economic sustainability.

The fluctuation of the information from the industry data can cause the industrial economy's fall. VAR learning helps identify the hike and the fall of the industry's economy through the classification of the related output. The time series data can help in finding the fall or the hike of the economy by its observed time of the factors which are reduced from the industry for the economic sustainability process. This data is invariantly handled using VAR in two different steps. First, the relation between the distinct factors based on time series is framed. And then, from that output, the economic level can be found by identifying whether it is increased or decreased from the actual target. The learning helps in verifying the relation output for the further process according to the time series framed. The fall can be identified based on the acquired time series data and its features, which predicates the relation output. The relation of the time series data can be classified into incremental and fall based on the economic outcome of the industry. The fluctuation between the rise and fall for the identified relationship is presented in Figure 3.

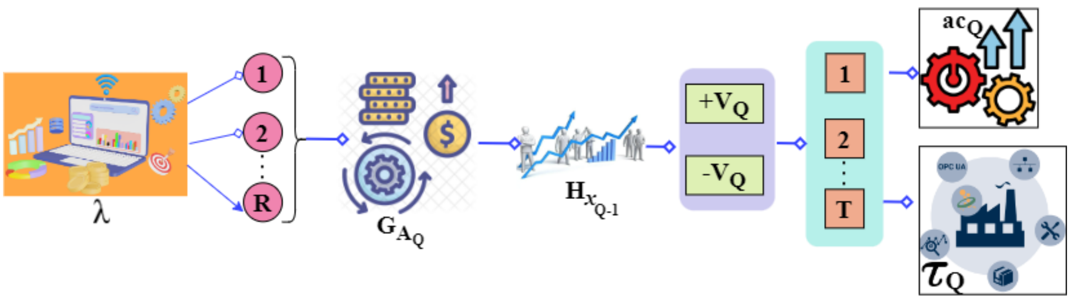

FIGURE 3. Fluctuation detection

The relationship process output helps identify the industrial economy's hike or fall, which is based on the acquired time series data such as production, transportation, supply, and market analysis data. Then VAR learning is used to find the relationship between the industry-extracted data, known as the time series data. Those time series data help in the process of finding the relation between the factors, and that output helps in identifying the fall of the economy (Figure 3). The process of finding the fall of the industrial economy from the output of the relation output by using the VAR learning method is explained by the following Equations (6) and (7):

$$a_Q = \sigma_{x_{Q-1}} + \tau_Q \tag{6}$$

$$\sigma = G^{-1}H \tag{7}$$

where $\sigma_{x_{Q-1}}$ is denoted as the calculation of the fall of the industrial economy, τ_Q is denoted as the calculated amount of time series data required to prevent the fall of the economy, and $G^{-1}H$ is denoted as the output of the acquired relation. Now from the output of the increased economic level, sustainability can be found. From the increased economic development outcome, sustainability can be identified where the maximum target is set as a benchmark for the upcoming process. In this sustainability, the maximum achieved target can be fixed as the benchmark for the further upcoming processes in developing the industrial economy. Here the economic level of the industry can be sustained at its achieved target and that target can be hooked as the touchstone for the new processes. With this benchmark from sustainability, the next process will be done to achieve better sustainability or to retain this benchmark.

The sustainability of economic development can be identified from the output of the incremental relation, which is diagnosed by the VAR learning process. The increased economic development of the industry helps in the static sustainability of the economic level. Based on the improvement, the output of the relationship process is set as a benchmark for economic sustainability. From this fixed sustainability, the further process is done to achieve the fixed target or to proceed better to achieve more than the fixed target. From the output of the increased economic level, sustainability can be found. From this sustainability, the economic level of the industry can be identified and the maximum achieved target can be set as the benchmark for the upcoming processes. From the increased economic development outcome, sustainability can be identified where the maximum target is set as a benchmark for the upcoming process. With the help of the time series data extracted from the industry it helps in the development of economic sustainability through the VAR learning process. Using the time series data features, the classification process is done to attain the maximum target, which is set by the output of the increased economic development. The relationship of the data can be found by using autoregression learning and that output is classified to find the industrial economy's hike or fall. From the increased hike of the relation, sustainability can be found and the maximum achieved target is fixed as the benchmark for the further processes in the industrial economic development. The process of obtaining sustainability through the output of the increased relation output by the VAR model is explained by the following Equations (8) and (9):

$$\tau_Q = G^{-1} v_Q(P) \tag{8}$$

$$B\left(\tau_Q, \tau_Q^1\right) = G^{-1} D \left(G^{-1}\right)^1 = Q \tag{9}$$

where P is denoted as the output of the hike of the relation output, $B\left(\tau_Q, \tau_Q^1\right)$ is denoted as the sustainability of the process, and D is denoted as the maximum target achieved. Now from the output of the fall of the relationship process between the time series data, the data add-on process will be done by adding up the time series data to achieve the target. Based on the improvement, the output of the relationship process is set as a benchmark for economic sustainability. If the fall of the relation output exists, then the time series data must be added to the further process of attaining the maximum target. The proposed model identifies incremental output post the forward time-series data for preventing sustainability falls. Again, the VAR learning method should add the time series data for the classification process. The learning regression is presented in Figure 4.

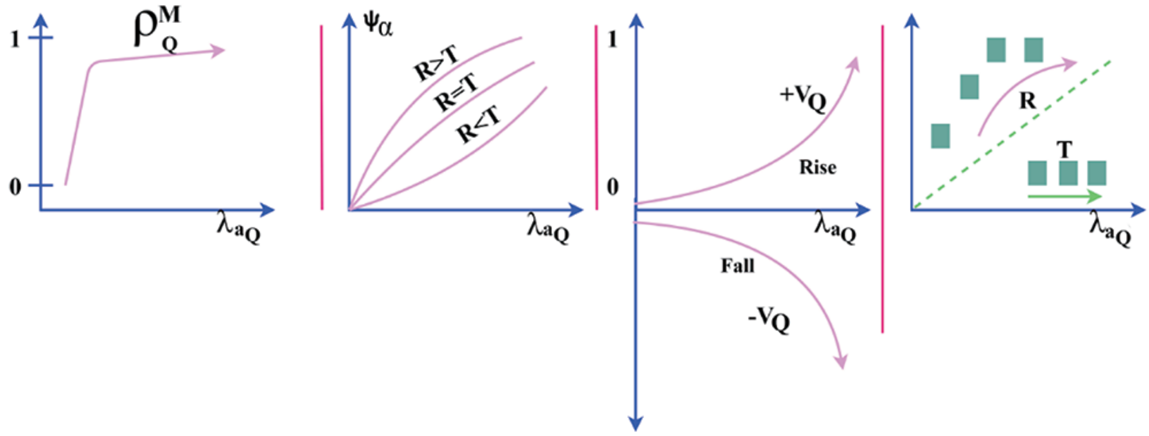

Figure 4. Learning regression for fall detection

If the fall occurs in the relation output, which is done by the autoregression learning process, then again the time series data should be acquired from the industry. Then VAR learning is used to classify the relation based on the time series framed. From the relation output, the increased target can be achieved through this reprocess by adding the time series data. By adding the data to the fall of the relation, the sustainability can reach its maximum target or it will reach the fixed target. Based on the improvement, the relationship is set as a benchmark for economic sustainability (Figure 4). The research models and forecasts the combined development of both immediate and prospective connections between firms using a VAR analysis. Figure 4 shows that the regression model is an effective tool for predicting time-series variables. The VAR model was used to conduct empirical research on the relationship between logistical growth and economic development. The model is often used for making predictions about intertwined time series systems and for assessing the dynamic influence of random disturbances upon such systems of variables. The key characteristic of the regression learning method is that it functions as a function of lagged values of all endogenous system variables, hence avoiding the need for structural modelling. The proposed model identifies incremental output post the forward time-series data for preventing sustainability falls. From the output of the fall of the relationship between the time series data, the data add-on process will be done by adding up the time series data. By adding up the time series data, the fall of the relation output can be reduced and the industrial economy can reach the maximum target or retain that target. The process of adding the data to prevent sustainability falls is explained by the following Equations (10), (11), and (12):

$$\left.\begin{aligned} \begin{bmatrix} \alpha_\sigma \\ \gamma_\sigma \end{bmatrix} = \begin{bmatrix} \sum\limits_{q=1} V_Q^R & \tau_Q^a \\ \sum\limits_{q=1}^{Q} V_a^a & \varepsilon_Q^R \end{bmatrix}^{-1} \begin{bmatrix} \sum\limits_{q=1}^{Q} V_Q^R & \tau_Q^M \\ \sum\limits_{q=1}^{Q} V_Q^a & \varepsilon_Q^M \end{bmatrix} \\ \begin{bmatrix} V_Q^Q \\ V_Q^M \end{bmatrix} = \pi\tau_Q \\ \pi = \begin{bmatrix} 1 & -\lambda & -\beta \\ -\tau & 1 & -\psi \end{bmatrix} \end{aligned}\right\} \tag{10}$$

$$\pi\phi\eta_\sigma = 0 \tag{11}$$

$$\phi_W = Q^{-1}\sum_{q=1}^{Q} \tau_Q\tau_Q^1 \tag{12}$$

where $\pi\phi\eta_\sigma$ is denoted as the output of the fall, and ϕ_W is denoted as the number of time series data added to retain or achieve the maximum target. By this proposed method, the fall can be reduced and the economic stability of the industry can be improved by using the VAR learning model. The maximum target attenuation is presented in Figure 5.

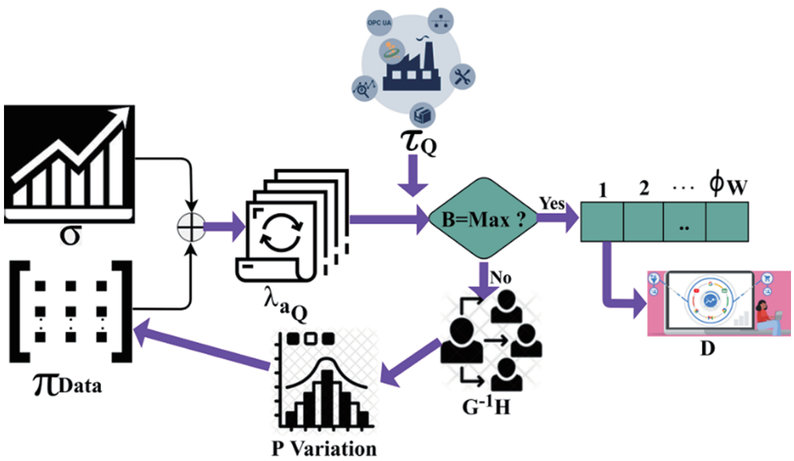

FIGURE 5. Maximum target attenuation

Handling fluctuating information requires multivariate functions for precise identification of economic sustainability. Therefore, this manuscript introduces an MDPM using VAR for balancing the fluctuating factors. The proposed model extracts differential information from varying time series related to the industrial economy. This data is invariantly handled using VAR in two different steps. Based on the improvement, the relationship is set as a benchmark for economic sustainability (Figure 5). The proposed model identifies incremental output post the forward time-series data for preventing sustainability falls. This model is validated using the metrics sustainability factor, processing rate, variation, processing time, and failures.

4. **Results and Discussion.** The results and discussion section uses the data from [29] to analyze the proposed model's performance. This data extracts the following information: area, industry code/name, establishments, revenue or business, quarterly and annual pay, and employers and non-employers establishments. From the considered data,

the "manufacturing industry" from 54 entries is used for processing. Therefore, the analysis considers 17 influencing factors (pay, employees, establishments, target, sales, revenue, and employees). For a specific time series, the data-acquiring process is illustrated in Figure 6.

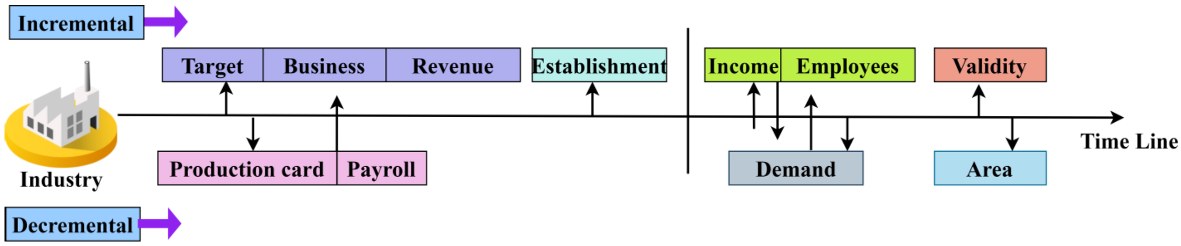

FIGURE 6. Data-acquiring representation

In the data-acquiring process, the considerations are either incremental/decremented, and at times it is both. The 17 factors are extracted over varying time intervals based on the quarterly and annual outcomes. Production and payroll rely on both incremental and decremented factors and the demand in the next time series. Therefore, sustainability based on these factors is expected to be stabilized for better economic growth (Figure 6). Now, the analyses for ρ_Q^M for the varying factors are presented in Table 1.

TABLE 1. Analyses for ρ_Q^M

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**
F1	1	0.62	0.63	0.43	0.36	0.43	0.53	0.52	0.48
F2	0.18	1	0.51	0.52	0.22	0.52	0.38	0.40	0.39
F3	0.26	0.76	1	0.68	0.65	0.49	0.62	0.53	0.62
F4	0.31	0.26	0.68	1	0.91	0.65	0.84	0.61	0.75
F5	0.42	0.69	0.73	0.71	1	0.62	0.59	0.75	0.85
F6	0.32	0.53	0.78	0.59	0.71	1	0.63	0.95	0.81
F7	0.56	0.42	0.54	0.43	0.95	0.53	1	0.86	0.69
F8	0.48	0.18	0.69	0.63	0.84	0.67	0.84	1	0.72
F9	0.52	0.63	0.75	0.71	0.69	0.52	0.76	0.92	1

The $F \times F$ factor has achieved high value. The other factors vary based on availability and market data. Therefore, the timeline varies the availability and decrements the features associated with $R = T$. This achieves stability in pricing and variation and thus reduces the case of regression. Therefore, the data requirements are increased across multiple P variations (Table 1). The above table represents the regression for ρ_Q^M and R are presented in Figure 7.

The ρ_Q^M is high only if $R > T$ is achieved compared to $R = T$ and $R < T$ conditions. Depending on the varying λ_{a_Q} in a day, the industrial economy fluctuates for a new ρ_Q^M. If this factor varies, then a new relationship is identified; the identification is performed only if the relationship between the factors is incremental/influential. Similarly, the R varies with $-V_Q$ compared to that of $+V_Q$. If a fall is observed, then R is varied for $H_{x_{Q-1}}$ instances for augmenting new data. Depending on the multivariate analysis, the validations are performed for G_{A_Q} other than a_Q. This stabilizes the sustainability factor preventing losses (Figure 7). In Figure 8, σ and τ_Q for the varying D are analyzed.

The data requirement and fall detection vary with the D achieved. In this D achievement process, the required σ and τ are analyzed. The time series data is invariably handled

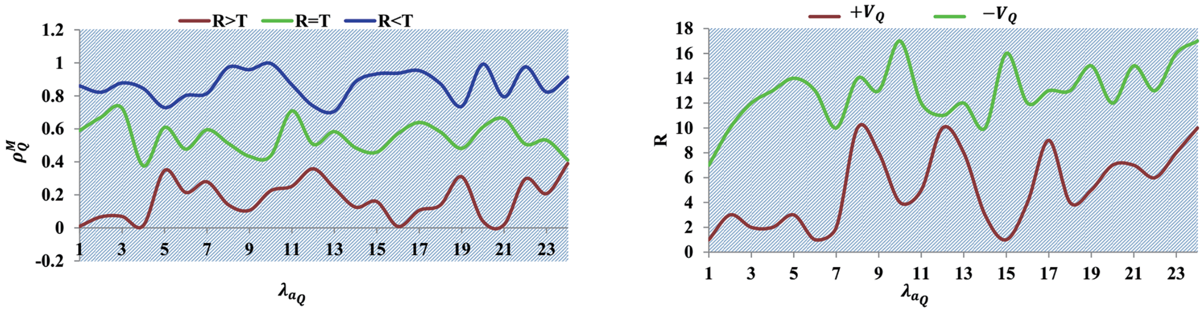

FIGURE 7. ρ_Q^M and R analyses

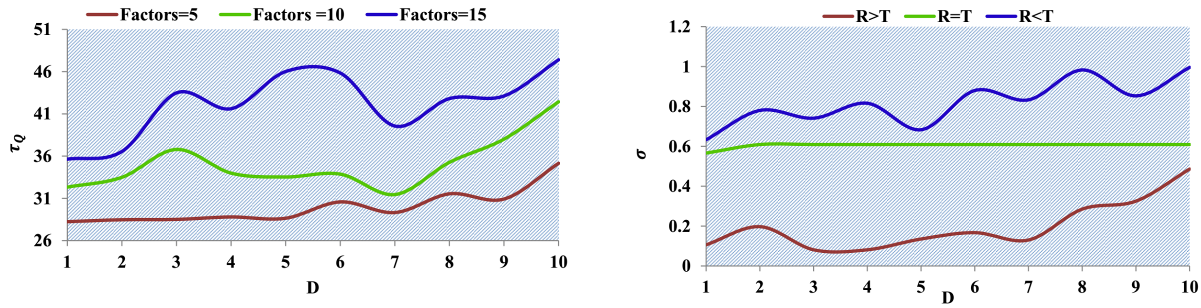

FIGURE 8. σ and τ_Q analyses

using multiple factors preventing $-V_Q$. The variable autoregression process $+V_Q$ or $-V_Q$ is identified for preventing multiple downfalls. Therefore, the regression is occupied based on augmented data to prevent high β_{M_Q}. In this process, the variants are handled using $G^{-1}H$ for maximizing data acquisition (Figure 8).

This subsection presents the comparative analysis using the metrics sustainability factor, processing rate, processing time, failure ratio, and data acquired. The X-axis variants are data inputs (100 to 1400) and considered factors (1 to 17). In the augmentation process, the methods MCDM [25], AP-MNR [26], and TSOM-EIS [20] from the related works section are considered.

4.1. **Sustainability factor.** The sustainability is better in this method by using Multivariate Data Processing Model (MDPM) using Vector Autoregression (VAR) for balancing the fluctuating factors. The sustainability of economic development can be identified from the output of the incremental relation, which is diagnosed by the VAR learning process. The increased economic development of the industry helps in the static sustainability of the economic level. Based on the improvement, the output of the relationship process is set as a benchmark for economic sustainability (Figure 9). From this fixed sustainability, the further process is done to achieve the fixed target or to proceed better to achieve more than the fixed target. From the increased economic development outcome, sustainability can be identified where the maximum target is set as a benchmark for the upcoming process. With the help of the time series data extracted from the industry it helps in the development of economic sustainability through the VAR learning process. Using the time series data features, the classification process is done to attain the maximum target, which is set by the output of the increased economic development.

4.2. **Processing rate.** The processing rate is better in this method by using the VAR model (Refer to Figure 10). For stabilized economic sustainability, different influencing

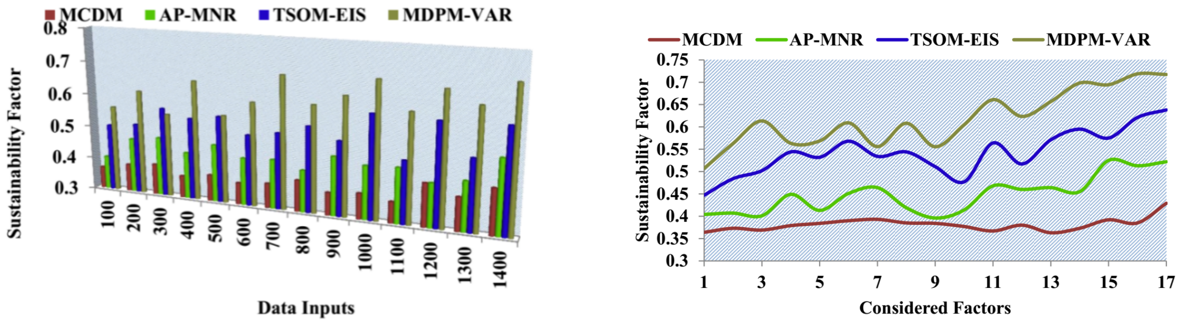

FIGURE 9. Sustainability factor

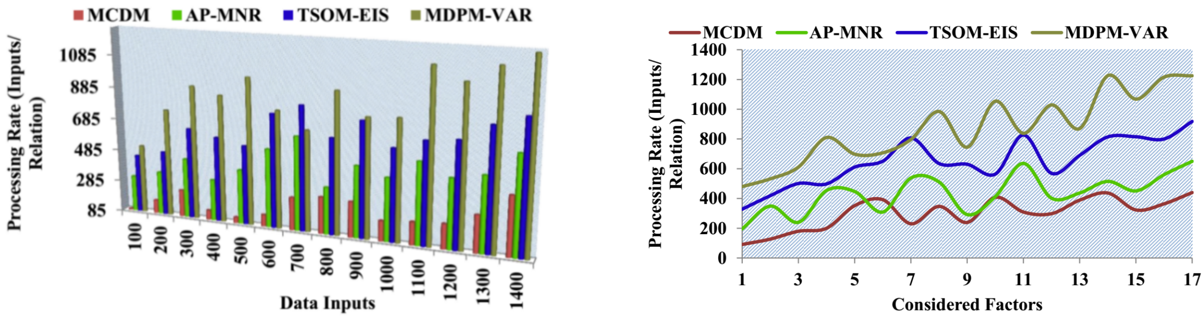

FIGURE 10. Processing rate

factors are to be considered with the varying time series information. Handling fluctuating information requires multivariate functions for precise identification of economic sustainability. Vector Autoregression (VAR) is introduced for balancing the fluctuating factors. The proposed model extracts differential information from varying time series related to the industrial economy. This includes production, transportation, supply, and market analysis data. This data is invariantly handled using VAR in two different steps. First, the relation between the distinct factors based on time series is framed. In the second step, the regression model for filtering the hike/increase in the relation output is performed. VAR in multivariate time series is used to analyze the system's variance, factor, and cluster. The autoregressive model expands their procedure to multiple time series so that the vector of present values of all data is modeled as linear and the sum of previous activities.

4.3. **Processing time.** The processing time is ancillary in this method by using the autoregression learning model for developing the industrial economy (Refer to Figure 11). The data is invariantly handled using VAR in two different steps. First, the relation between the distinct factors based on time series is framed. If the price is high, the demand reduces, if the demand increases on this criterion the relationship process takes place. The relationship process is done for the factors which are extracted from the industry. VAR learning which is used in the classification of the data by finding the relation between the distinct factors helps in observing the time of the data which is produced by the industry. This learning algorithm helps in finding the continuous observation of the time series data for the procedure of finding the relation between the factors. VAR is a procrastinating algorithm that can be used when two or more time series influence each other. It is used to observe the time of the demand, supply, and production data extracted from the industry. The VAR helps in finding the time taken for the factors to obtain its features in the industry to improve economic development.

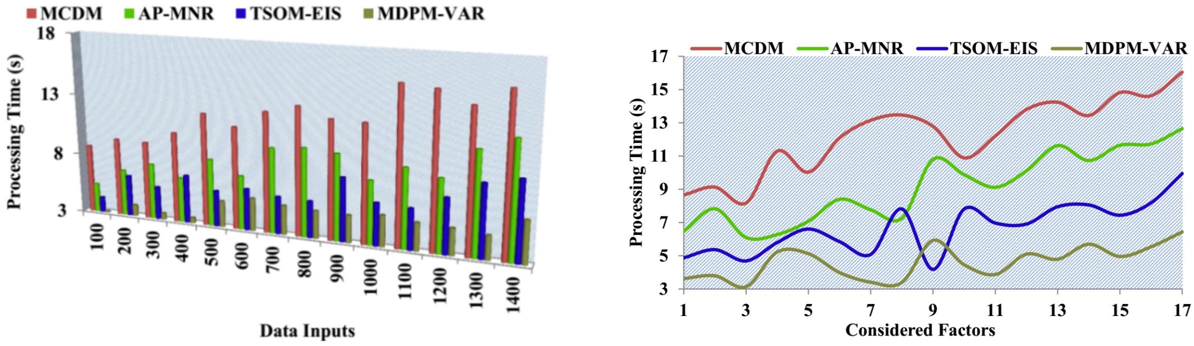

FIGURE 11. Processing time

4.4. **Failure ratio.** The economic fall is less in this method by using the vector autoregression model (Refer to Figure 12). The regression model for filtering the hike/increase in the relation output is performed. The relationship is set as a benchmark for economic sustainability based on the improvement. The proposed model identifies incremental output post the forward time-series data for preventing sustainability falls. From the output of the fall of the relationship between the time series data, the data add-on process will be done by adding up the time series data. If the fall of the relation output exists, then the time series data must be added to the further process of attaining the maximum target. The proposed model identifies incremental output post the forward time-series data for preventing sustainability falls. Again, the VAR learning method should add the time series data for the classification process. From the relation output, the increased target can be achieved through this reprocess by adding the time series data. By adding up the time series data, the fall of the relation output can be reduced and the industrial economy can reach the maximum target or retain that target.

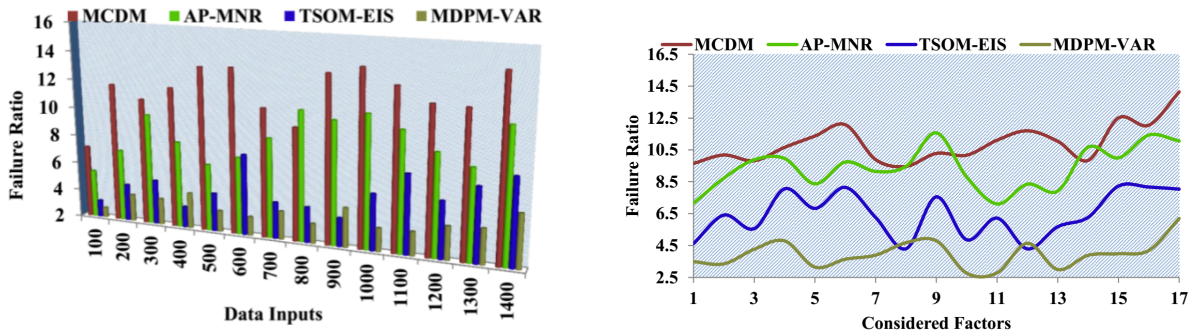

FIGURE 12. Failure ratio

4.5. **Data acquired.** The data acquired from the industry is high in this industrial economic development process by using the VAR model (Refer to Figure 13). The proposed model extracts differential information from varying time series related to the industrial economy. This includes production, transportation, supply, and market analysis data. The market, transportation supply, and production data are known as time series data. In this, the time of the data which is extracted from the industry is observed. Time series data is the collection of observations obtained through repeated processes over time. The market data denotes the number of chattels required for the consumers, transportation data represents the process of acquiring and preparing the stuff to deliver for the further process and the production data denotes the manufacturing process of the entire chattels. Autoregression learning is used to determine the sustainability of economic development

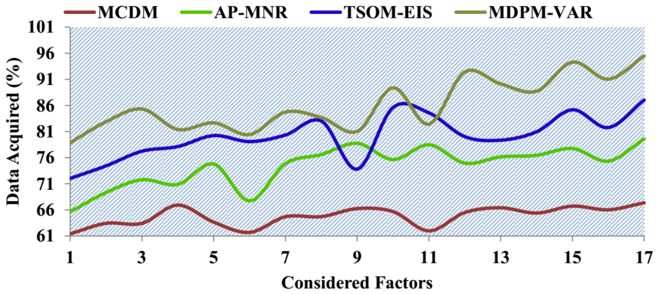

FIGURE 13. Data acquired

TABLE 2. Comparative summary of data inputs

Metrics	MCDM	AP-MNR	TSOM-EIS	MDPM-VAR	Findings
Sustainability factor	0.435	0.519	0.608	0.7211	10.02% High
Processing rate (inputs/relation)	449	690	896	1236	7.52% High
Processing time (s)	15.82	12.32	9.42	6.438	8.09% Less
Failure ratio	14.52	11.21	8.02	5.711	11.08% Less
Data acquired (%)	67.36	79.58	87.05	95.475	8.74% High

TABLE 3. Comparative summary of considered factors

Metrics	MCDM	AP-MNR	TSOM-EIS	MDPM-VAR	Findings
Sustainability factor	0.429	0.522	0.638	0.7173	9.38% High
Processing rate (inputs/relation)	440	650	918	1225	7.56% High
Processing time (s)	16.05	12.65	9.95	6.434	8.31% Less
Failure ratio	14.14	11.06	8.04	6.199	7.34% Less

in the industry through the relationship process. From the time series data, its features can be classified to detect the economic status and the further steps to prevent sustainability falls. The comparative analysis summary is presented in Tables 2 and 3 for the data inputs and considered factors.

5. **Conclusions.** This article introduced a multivariate data processing model using vector autoregression to improve the industrial economy with better sustainability. In this model, various data including production, supply, market demand, and their corresponding fluctuating factors, are accumulated first. This accumulation is purely a time series based on which the rise and fall in the economy are analyzed periodically. The periodic analysis is performed using linear regression and vector models to prevent failures. This is carried out by identifying the relationship between the influencing factors wherein the hike or fall in the economy is validated. Considering the maximum target achieved in different time series and accumulated data, autoregression is performed for accumulating further data. This accumulated data balances the estimated fall in the consecutive time series. The regression is modified using the newly identified relationships between the influencing factors for reducing the processing time. One limitation of the multi-variate VAR model is that it cannot be used to depict connections between variables as existing at any given moment in time which affects the economic models used in industrial sector development systems. In future, the industrial expansion, protection of the environment,

social contentment, and efficient resource use are the four pillars of sustainable development, and each has to be tweaked, improved, and rebuilt to achieve harmony. When energy sources lose their economic supremacy, the major recommendation for government planners is the growth of other economic sectors. For the varying considered factors, the proposed model improves the sustainability factor by 9.38%, the processing rate by 7.56%, and reduces processing time and failure ratio by 8.31% and 7.34%, respectively.

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